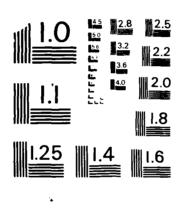
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COMPARING REGRESSION EQUATIONS ACROSS
TRAINING PROGRAMS: AN EMPIRICAL STUDY
OF PRIOR SELECTION EFFECTS AND
ALTERNATIVE PREDICTION
COMPOSITES

Stephen B. Dunbar

ONR Technical Report 86-1

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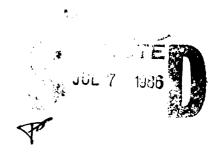


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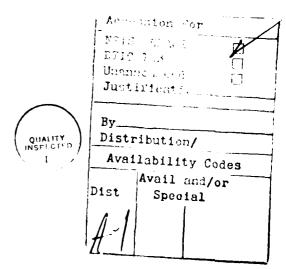
These predictions are considerably more homogeneous and consistent with course content when a procedure for simultaneous estimation of regression coefficients is used and when regression coefficients are adjusted for incidental selection. Implications of these findings for the development of alternative prediction composites are discussed and illustrated by examining alternatives to the present ASVAB composite for selecting trainees in clerical programs.

# COMPARING REGRESSION EQUATIONS ACROSS TRAINING PROGRAMS: AN EMPIRICAL STUDY OF PRIOR SELECTION EFFECTS AND ALTERNATIVE PREDICTION COMPOSITES\*

Stephen B. Dunbar The University of Iowa

# <u>Abstract</u>

This study examines the possible magnitudes of incidental selection effects on prediction equations for performance in twenty-seven technical training programs in the Marine Corps. Selection composites for Forms 8, 9, and 10 of the Armed Forces Vocational Aptitude Battery (ASVAB) are shown to yield widely varying predictions of final grades in training when the usual least-squares regression equations are examined. These predictions are considerably more homogeneous and consistent with course content when a procedure for simultaneous estimation of regression coefficients is used and when regression coefficients are adjusted for incidental selection. Implications of these findings for the development of alternative prediction composites are discussed and illustrated by examining alternatives to the present ASVAB composite for selecting trainees in clerical programs.



\*Support for this research was provided under contract N00014-83-C-0514 with the Personnel Training Branch of the Office of Naval Research, Melvin R. Novick, principal investigator. The author is grateful to Melvin R. Novick for insightful comments and discussion on the issues addressed in this study and for his support and encouragement over the past several years. He is also grateful to Ming-mei Wang, who furnished the computer program used in the heteroscedastic m-group regressions.

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Comparing Regression Equations Across Training Programs:
An Empirical Study of Prior Selection Effects and
Alternative Prediction Composites

# Introduction

In the context of criterion-related validity studies, the importance of comparisons of regression equations for groups differentiated by characteristics irrelevant to criterion performance has been underscored recently in the new Standards for Educational and Psychological Testing (AERA, APA and NCME, 1985). When feasible, it is recommended that studies of differences between prediction systems include comparisons of predicted criterion scores at various points on the regression function for groups of substantive interest, in addition to the more common comparisons of validity coefficients.

It has been clear for some time that any differences observed in such comparisons can be caused by a number of factors, not all of which make the desired assessments of differential prediction or predictive bias transparent. Linn and Werts (1971), for example, showed that differences between subgroup regression equations can be caused by failure to include a relevant predictor in the equations being compared, i.e. by incorrect specification of the prediction model being determined. This is the case when a variable that is related to performance on the criterion is correlated with subgroup membership and is omitted from the regression equation. Indeed, it has been suggested by several authors (e.g. Hunter & Hunter, 1984 and Gamache & Novick, 1985) that the problem posed by differences between subgroup predictions is best handled by respecifying the prediction model, either by adding or deleting appropriate independent

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variables such that subgroup differences are reduced. Indeed, Gamache and Novick (1985) argue that differences between prediction systems are often effected by the inclusion of variables having weak relationships with the criterion and strong ones with group membership.

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In studies of predictive bias alluded to above, another potential cause of contrasting regression equations is the presence of incidental selection effects. When a variable, or set of variables, is correlated with both predictors and the criterion, and the distributions of such variables in the subgroups are not similar because the degrees of range restriction vary, then differences are likely to surface in the comparison of regression equations. Linn (1983) illustrates this phenomenon specifically in the context of predictive bias, although the problem has been familiar to personnel psychologists for many years. It too can be understood as a slightly different reflection of the specification error discussed previously. Here the error lies in failure to consider the selection process as contributing to possible differences between prediction systems.

In addition to complicating the issue of predictive bias, the effects of incidental selection can wreak havor on efforts to improve the selection process through assessments of the accuracy of alternate predictors of criterion performance. As illustrated by Dunbar and Linn (1985), a variable that was not used for selecting persons from the applicant pool may appear to be a better predictor of performance than the actual selection variable simply because its range is less restricted than the range of the selection variable. For this reason, judgments of the quality of alternate predictor variables on the basis of selected samples must often be tempered by careful consideration of the sample selection process.

Research on personnel selection in the military is typically conducted in the face of problems such as those described above. The purpose of this paper is to compare the regressions of performance criteria on selection composites from the Armed Services Vocational Aptitude Battery (ASVAB), Forms 8, 9 and 10 for a host of technical training programs in the Marine Corps. In addition to the usual comparisons of unadjusted estimates of slopes and intercepts, comparisons will be made of estimates that have been corrected for the possible effects of incidental selection by two adjustment procedures. The intent of examining both unadjusted and adjusted estimates is twofold. First, it will provide an indication of the magnitude of differences that could be considered due to different degrees of range restriction on the predictor variables of interest. Second, it will provide an alternative view of the accuracy of various ASVAB selection composites for heterogeneous training programs that is less influenced by the fact that selected samples were used in the calculations.

# Related Research

Comparisons of the criterion-related validity of selection instruments across job categories have been enriched by developments in the meta analysis of locally-based validity studies known to personnel psychologists under the generic heading of validity generalization. No attempt is made here to review the vast amount of work done in this area during the past five years (cf. Linn & Dunbar, 1985). In general, this work focuses on identifying what are considered artifactual sources of variability in the observed predictive validities of selection tests used

for screening applicants for jobs or admission to educational programs. Of the artifactual sources of variation in observed validity coefficients that are usually addressed in validity generalization research, the one most relevant to the concerns of the present study is that due to varying degrees of selectivity in the technical training program for which validity evidence is sought. This study differs from most empirical work in the validity generalization tradition in its focus on regression equations in addition to validity coefficients, so it might be more appropriate to term the present study one of relationship generalization and, moreover, one that considers only one of the several sources of situational specificity in regression equations mentioned in the original developments of Schmidt and Hunter (1977).

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In most validity generalization research, the standard approach to range restriction involves the use of Pearson's correction for explicit selection on the predictor described by Thorndike (1949). This results in an adjusted predictor-criterion correlation that is higher than the original value as a function of the ratio of the standard deviations in the unselected population and selected sample. When the selection process is known to be based on other variables in addition to the predictor of immediate concern, and such variables are positively correlated with the predictor and criterion, this adjustment is likely to be conservative, i.e. underestimate the population correlation (Linn, 1968; Linn, Harnisch & Dunbar, 1981a). This has led some researchers to suggest the use of Lawley's multivariate adjustment procedures, which accomodate multiple predictors and criteria in addition to providing corrections for the regression slopes and intercepts that are also affected by selection on a third variable.

An issue of great concern regarding multivariate correction procedures is their accuracy under conditions in which the assumptions of linearity and homoscedasticity of the regression of incidental on explicit selection variables are violated, particularly when selection is severe. Lord and Novick (1968) were among the first to caution against heavy reliance on adjustment procedures because of potential overcorrections due to reduced variance around the regression line at extreme predictor scores. This was considered an acute problem whenever the ratio of selection variable standard deviations in the unselected population and selected sample exceeded 1.4. Subsequent empirical studies have documented such overcorrections in the presence of heteroscedasticity and extreme degrees of range restriction (Novick & Thayer, 1969; Greener & Osburn, 1979; Dunbar, 1983). However, simulation studies have also shown that the tendency toward overcorrection can be overshadowed by a complementary tendency toward undercorrection when the slope of the regression line decreases at extreme scores on the predictor. When the effects of these types of non-linearity and heteroscedasticity are considered simultaneously, the result is often a conservative estimate of the population correlation (Dunbar, 1983). The same trend has been found in corrections of regression slopes and intercepts. The question of violated assumptions is considered at length by Dunbar and Linn (1985), who summarize the literature on this matter and argue that multivariate adjustments are likely to be conservative in the context of validating selection tests in the military.

Further support for the use of adjustment procedures comes from comparing their performance to that of methods for handling range restriction that stem from different assumptions about the regressions of

substantively interesting variables on selection variables. Linn, Harnisch and Dunbar (1981b) and Linn and Hastings (1984) illustrate the use of an adjustment procedure that is based on empirical relationships between observed validity coefficients and characteristics of predictor score distributions that reflect the presence of range restriction. The latter study, in particular, found point estimates of the predictive validity of the Law School Admission Test (LSAT) obtained by the empirically-based procedure to be quite similar to those obtained by the multivariate adjustment procedure. In a similar vein, Braun and Szatrowski (1984), used an elaborate method for rescaling criterion variables used in locally-based validity studies that links or equates criterion scores in similar groups to create what they call a universal criterion scale. Criterion scores on the universal scale were then used to validate the LSAT and undergraduate grades as predictors of law school performance. Again, the results showed the universal scale approach to give estimates of predictive validity that were similar to those provided by the Pearson-Lawley adjustments, even though the two methods are based on quite different assumptions.

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Even though a negative bias may remain when using the multivariate corrections, it doesn't follow that a population value cannot be overestimated with an adjustment procedure. It is well known that the mean squared errors of adjusted slopes, intercepts, and correlations can be much larger than those of unadjusted values (Dunbar & Linn, 1985).

Appropriate caution, therefore, needs to be emphasized in the interpretation of any coefficient that has been 'corrected' for range restriction.

# Method

The data used in this investigation consist of ASVAB subtest and composite scores and final course grades for Marine Corps trainees in 27 different technical training programs leading to specific job classifications upon completion of training. Table 1 lists the training specialties included along with sample sizes and relevant ASVAB selection composites. Training programs are categorized on the basis of the ASVAB composite used for selection, forming training cohorts such as mechanical or clerical specialties. All training programs included in this study report performance measures on a nominal scale of 0 to 100. Sample sizes ranged from 109 to 1791, with a mean of 336. In order to restrict possible sources of differences between regression equations for individual programs, only white males were included in the samples for which analyses are reported. Studies showing the importance of gender- and race-related differences for military technical training data have recently been conducted by Dunbar and Novick (1985), Curtis, Foley and Monzon (1985), and Houston and Novick This problem receives further attention in discussion of the results of the present study.

Insert Table | About Here

# Procedure

All analyses were conducted using final course grades, standardized within each training program, as criteria and selected ASVAB composites as

predictors. Least-squares and Bayesian m-group estimates of slopes and intercepts from the regression of standardized course grades on the ASVAB composites were first determined with no adjustments made for the possible effects of incidental selection. These were then compared to estimates derived from two procedures for correcting regression coefficients for incidental selection, (1) the standard Lawley multivariate correction formulas, using statistics from three different reference populations as estimates of the variances and covariances of ASVAB subtests in an unselected group, and (2) a modification of the Heckman (1979) approach to incidental selection, using a logistic instead of a probit regression in the first stage of his two-stage procedure. In the case of the Heckman adjustments, data from the entire sample were used in the logistic regressions in order to estimate selection terms for trainees in individual programs.

The modification of Heckman's approach to sample selection bias was straightforward. In the original Heckman (1979) two-stage procedure, a selection term is estimated for each observation that describes the chance of the observation's being lost in the sample selection process. This term is estimated using a probit regression of the dichotomous indicator of presence in the sample (1 = selected, 0 = not selected) on the set of posited selection variables. Heckman (1979) specifically used a hazard rate, the ratio of the ordinate of the normal density to the probability of non-selection, as the term entered along with predictors of substantive interest in a least-squares regression. The least-squares regression is adjusted for selection bias by inclusion of a selection term as the formerly 'missing' variable. The modification used in this study simply substituted a logistic regression for the probit regression in the first

stage of Heckman's method and specified the selection term using the relation

$$log{[1 - e(x)]/e(x)} = a + b^{x},$$

where a and b represent the parameters of the logistic regression and X represents the vector of posited selection variables. This term simply represents the log-odds of non-selection and has been used by Rosenbaum and Rubin (1983a, 1983b) for bias adjustment in observational studies, with e(x) = Prob(Y=1|X) termed the propensity score. The relevance of their work to selection bias in criterion-related validity studies is obvious, but seems not to have been described in any explicit manner in the literature.

In the present study, all ASVAB subtests (that in varying combinations make up composite measures) were treated as explicit selection variables in both the Lawley and Heckman adjustment procedures. Thus, the covariance matrix of subtests in each of the designated reference populations was obtained in implementing Lawley's adjustment. In the modification of Heckman's approach, the subtests were considered predictors of the dichotomous criterion in the logistic regression stage. No attempt was made to determine empirically an optimal combination of the subtests in fitting the logistic regressions; optimality was sacrificed in the interest of using a common procedure for all training cohorts.

Because a major interest was the effect of incidental selection on predicted criterion scores (for different predictors within the same

program and for common predictors across different programs) there was an interest in evaluating the structure of predicted scores based on slopes obtained under various adjustment procedures and in determining differences in this structure for the various training programs. This was accomplished by means of a three-way or weighted metric multidimensional scaling (Carroll & Chang, 1970) of average absolute differences between predicted scores obtained from the six ASVAB selection composites using unadjusted and adjusted regression equations.

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## Results

The principal results of this study concern the estimates of regression slopes and intercepts under various conditions. The Lawley adjustments of least-squares and m-group coefficients were based on one of three potential reference groups: (1) the data base of Marine Corps trainees available for the present study (a surrogate accession population), (2) the 1980 Youth population with the lower 10 percent of the AFQT distribution deleted and (3) the full 1980 Youth population. The modified Heckman results, in contrast, base any adjustment only on individuals in the present database. Because complete results of all regression analyses are unwieldy, only highlights will be discussed in the body of the present report.

Trends found to be typical of many of the findings are illustrated in Figures 1 and 2, which contains box-and-whisker plots of the distributions of regression slopes in the least-squares analysis for the 27 training programs. In these plots, the box represents the middle 50 percent of the distribution, while the whiskers extend to the 5th and 95th percentiles.

The plots in Figure 1 describe results of the unadjusted least-squares analyses, while those in Figure 2 describe results of the unadjusted m-group analyses.

The distributions of unadjusted slopes given in Figure 1 depict a scene that is common in criterion-related validity studies that compare many groups or job classifications. The general appearance is one of selection tests that lead to a heterogeneous set of predicted criterion scores depending on combinations of job classifications and predictor variables. Variance explained in the criterion by the various ASVAB composites ranged from less than 1 percent for the clerical composite, CL, in a combat specialty to 29 percent for the electrical composite, EL, in a clerical specialty. Although it was not the case that the selection composite used in particular specialty areas explained the least variance in the criterion, for many of the groups under examination a composite other than the one used for selection had the appearance of yielding more accurate predictions, in terms of variance accounted for, when the unadjusted least-squares equations are interpreted. Incidental selection effects are one possible explanation for this outcome.

As can be seen from the figure, there appears to be substantial variation in the sizes of performance increases as a function of ASVAB composite scores. Most notable in this regard are the clerical and electrical composites, CL and EL. CL appears to be the least effective predictor of training grades over all job classifications, although some exceptions do exist, while EL appears to be more effective than any other single predictor for the majority of groups. Note that EL is not used as a selection composite for any of the groups included in this study.

Insert Figure 1 About Here

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The results of Bayesian m-group regression analyses are illustrated by the plots in Figure 2. The estimates of slopes depicted in the figure were derived in a manner similar to that described by Dunbar, Mayekawa and Novick (1985), which treats job specialties using a common selection composite as an exchangeable sample from a population of such specialties. Thus, the five clerical training programs, eight combat programs, and so on, were grouped and regression parameters for individual programs were estimated simultaneously within each of the resulting groups. Unlike the Dunbar, et al. analyses, those in the present study were performed using an algorithm similar to the one described by Rubin (1980) that does not assume between group homoscedasticity of the error variances, but instead estimates the mean and variance of the prior distribution for the error variance from the data.

Insert Figure 2 about here

As can be observed from the plots of m-group slopes, there was much greater homogeneity in the slopes of regression lines for the various groups using the Bayesian approach. A similar result was found for the intercepts. Although it was not the case that slopes associated with common composites across groups were identical, some degree of shrinkage

of estimates toward a common value was evident from the results of the Bayesian analysis. Of course, this is to be expected as a consequence of the principle of exchangeability of groups using the same ASVAB composite for recruit selection. Note that CL continued to have the smallest slope, on average, of any ASVAB composite.

The effects of Lawley's multivariate corrections for slopes and intercepts affected by incidental selection are summarized in Table 2, which gives observed means and standard deviations of the distributions of regression slopes across programs under various adjustment conditions for the six ASVAB composites considered in this report. Several important findings can be noted with respect to these statistics. The first is the obvious increase in average slopes as the reference population used to effect the Lawley procedure broadens in the range of talent represented. When all trainees in the present data base are considered the reference group, the increases are not striking in magnitude. However, the use of the 1980 Youth Population (with or without the bottom 10 percent on AFQT) results is a more dramatic increase, on average, in the slopes of the regression lines associated with each ASVAB composite. In addition, the pattern of increases is nearly identical for the adjustments of leastsquares and m-group coefficients. The second outcome of interest in the table concerns the standard deviations of the observed and adjusted coefficients. Also as expected, the variability of slopes across training programs increases when the Lawley adjustments are used. However, because the m-group coefficients are less variable to begin with, the increase noted in the standard deviations for the adjusted Bayesian coefficients is not drastic. In all cases, the standard deviations of the least-squares coefficients are greater than those of the m-group coefficients when the

same reference population is used, suggesting that a useful way of exercising control over increases in the variability of adjusted values is to take advantage of exchangeability among groups when it can be assumed to exist.

Insert Table 2 About Here

The last result of interest in Table 2 concerns the performance of the two-stage procedure marked as condition MHK for modified-Heckman. The average slopes obtained with this adjustment procedure more closely resemble the means in the unadjusted conditions, either least-squares or m-group, than they do the means under any other condition. In addition, the standard deviations across programs in several cases are as large or larger than those obtained when the Lawley correction was used with the least-squares coefficients. In other words, the results in Table 2 indicate that this approach, as implemented in the present study, had little effect on the prediction equations, on average, but at the same time yielded more widely varying equations for individual programs.

# Structural Analysis of Predicted Scores

An indication that differences between regression equations within programs were reduced on adjustment for incidental selection was observed in results from the three-way MDS (INDSCAL) analyses. Because the structure of only six predicted scores was examined for each group, all INDSCAL

solutions obtained were restricted to two dimensions, with principal interest in the extent to which the second dimension was needed to explain either the structure of differences between predicted scores within a training program or to explain differences between programs in that structure.

Table 3 presents goodness-of-fit statistics for the INDSCAL solutions under the nine adjustment conditions. The values of STRESS are based on Kruskal's (1964) fit statistic for multidimensional scaling, which approaches zero as the scaling solution obtained becomes a better representation of the observed data. The values of RSQ represent the proportion of variance in the observed prediction differences explained by the two dimensions of the INDSCAL solutions and are included for ease of interpretation.

As might be expected on the basis of results already presented, the two-dimensional solutions tend to fit the observed data better as the degree of adjustment made by the Lawley correction increases. With respect to both the least-squares and m-group coefficients, values of STRESS steadily decrease as the reference population used to adjust the regressions changes from the surrogate accession group, to the truncated 1980 Youth group, to the entire 1980 Youth group. These results suggest that the structure of predicted scores is more easily explained by a solution with a small number of dimensions when adjustments have been made for incidental selection. In other words, the ASVAB composites tend to give more similar indications of expected performance when expectations recognize the possible effects of incidental selection. The value of STRESS associated with the INDSCAL solution for modified Heckman analysis

again reflects the erratic performance of the method as implemented in this study.

Similarities between training programs in the structure of prediction differences are shown in Figure 3, which contains plots of the weights estimated for individual programs in the INDSCAL solution for two adjustment conditions. These weights describe the salience of each dimension in determining the distance between points that represent selection composites in the two-dimensional solution, and in the present context they provide a means of comparing the 27 training programs. The sums of the squared weights themselves equal the proportion of variance explained by the solution for particular programs and is represented geometrically by the distance of points in the plots from the origin. Figure 2 gives results from the unadjusted m-group regression equations and the same equations adjusted for incidental selection using the full 1980 Youth Population as the base group.

Insert Figure 3 About Here

The plots in Figure 3 illustrate the largest contrast observed between an unadjusted and adjusted solution. The plot for the unadjusted condition shows greater differences between programs in the structure of differences between predicted scores obtained from the six selection composites. Differential weighting of the two dimensions in the MDS solution appears to be more of a rule than an exception for the unadjusted regression equations. In contrast, the plot for the adjusted equations

shows a greater tendency for larger weights on the first dimension, and only a few programs with sizeable proportions of variance accounted for by the second dimension. Plots for other adjustment conditions were similar in revealing smaller contrasts across training programs.

### Discussion

The contrasts illustrated in this paper provide an indication of the possible effects of incidental selection on the observed regessions of training course grades on selection tests in common use in the military. With a homogeneous subject pool as a base group, ASVAB composite variables were shown to yield increasingly similar predictions of criterion performance after adjustment for selection effects. However, even with the full 1980 Youth Population as a reference group, the INDSCAL analyses did reveal small program-to-program differences in the structure of predicted scores, and these differences seemed related to the salience of the second dimension in the MDS solutions. On inspection it was found that four of the six training programs with the largest weights on dimension II were Aviation specialties, while four of the six with the smallest weights were General or Combat specialties. The former group differs in having greater emphasis placed on specific subject matter such as electrical and mechanical information.

Following adjustment for indirect range restriction the average slopes for ASVAB selection composites were quite similar, with the lone exception of CL, the Clerical/Administrative composite, which in all analyses appeared to be the poorest predictor of success in training.

This finding may be due to the fact that two of the four subtests used to form this composite are speeded (Numerical Operations and Coding Speed). Speededness has often appeared as a group factor in studies of human abilities. It is likely that this factor is not well represented in the criterion variable used in the present study and its absence may in part explain the relatively poor performance of CL as a predictor.

The two-stage approach adapted from Heckman (1979) did not fare well as a routine adjustment procedure for incidental selection effects. Such disappointing results may well be due to the fact that a common set of selection variables was used in the logistic regression stage and the selection process for individual programs was thereby modeled inaccurately. They may also be a reflection of the fact that the Heckman approach can be subject to large ammounts of sampling error, particularly in cases where the variables used in the logistic regression stage are closely related to those used in the second stage and where sample sizes not extremely large. Both of these conditions were present in this study. In contrast, the behavior of the Lawley corrections appeared to be much more regular and predictable.

Final comments concern the generalizability of the findings of the present study. Although greater similarities between predicted scores were found following adjustment for incidental selection, they were obtained using data from a homogeneous subject pool. To the extent that subject variables such as sex and race interact with ASVAB composites in the prediction of training success (cf. Dunbar & Novick, 1985; Houston & Novick, 1985), greater differences between regression lines using heterogeneous groups would be likely even after adjustment for incidental selection. The intent of the present analysis was to show how much

similarity might be expected for subjects with common backgrounds and even in this case some differences between groups could be detected.

A second concern regarding generalizability relates to the choice of a reference population on which to base adjustments for range restriction. The choice here probably depends on the role one sees the Lawley adjustments playing in test validation. In large organizations in both government and industry, correcting for restriction of range serves a need for comparability as well as a need for reduced bias in parameter estimation. It was in the interest of comparability, across services, that Dunbar and Linn (1985) suggested the use of the 1980 Youth Population as a reference group. One should recognize, however, that an accession population might be more appropriate in some settings.

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Table 1

Training Programs, Sample Sizes and Operational Selection Composites

Training Program	Sample Size	Composite	
Administrative Clerk	205	Clerical (CI	
	180		
Communications Center	<u>-</u>		-
Supply Stock	446	Clerical (CI	
Aviation Supply	269	Clerical (CI	
Finance Records Clerk	135	Clerical (CI	- 1
Rifleman A	1791	Combat (CO	
Rifleman B	1013	Combat (CO	
Machine Gunner A	391	Combat (CO	))
Machine Gunner B	141	Combat (CO	))
Mortor Man A	407	Combat (CO	))
Mortor Man B	172	Combat (CO	))
Antitank Assault A	439	Combat (CO	))
Antitank Assault B	170	Combat (CO	))
Fire Control	179	Field Artillery (FA	1)
Amphibian Crew	286	Field Artillery (FA	7)
Ammunition Storage	118	General Technical (GT	(1
Basic Food Service	341	General Technical (GT	(1
Aviation Ordnance	308	General Technical (GT	(1
Eng. Equipment Mechanic	136	Mechanical Maintenance (MM	1)
Eng. Equipment Operator	36 <b>2</b>	Mechanical Maintenance (MM	1)
Combat Engineer	138	Mechanical Maintenance (MM	1)
Tracked Vehicle Repair	122	Mechanical Maintenance (MM	I)
Basic Auto Mechanic	343	Mechanical Maintenance (MM	I)
Aviation Machinist	421	Mechanical Maintenance (MM	()
Aviation Equipment Mechanic	c 109	Mechanical Maintenance (MM	- •
Basic Helicopter	320	Mechanical Maintenance (MM	ı)
Aviation Crash Crew	129	Mechanical Maintenance (MM	1)

Table 2

Means and Standard Deviations of Regression Slopes under
Various Adjustment Conditions

Adjustment	Selection Composite			
Condition	CL	CO	<u>EL</u>	
LS0	.0155 (.0062)	.0252 (.0065)	.0323 (.0107)	
LSl	.0181 (.0065)	.0283 (.0088)	.0341 (.0119)	
LS2	.0243 (.0077)	.0307 (.0089)	.0344 (.0119)	
LS3	.0255 (.0076)	.0337 (.0101)	.0368 (.0122)	
MG0	.0151 (.0045)	.0254 (.0043)	.0314 (.0077)	
MG1	.0178 (.0054)	.0284 (.0075)	.0337 (.0095)	
MG2	.0239 (.0070)	.0307 (.0083)	.0341 (.0105)	
MG3	.0253 (.00 <sup>-</sup> 1)	.0337 (.0091)	.0365 (.0111)	
мнк	.0179 (.0149)	.0240 (.0076)	.0327 (.0108)	
	FA	GT	ММ	
LS0	.0296 (.0089)	.0271 (.0092)	.0283 (.0098)	
LSI	.0309 (.0104)	-	.0290 (.0107)	
LS2	.0333 (.0106)	.0320 (.0101)		
LS3	.0333 (.0102)	.0323 (.0101)	.0336 (.0107)	
MG0	.0297 (.0064)	.0268 (.0061)	.0281 (.0072)	
MG1	.0308 (.0086)	.0286 (.0071)	.0290 (.0093)	
MG2	.0333 (.0094)		.0305 (.0096)	
MG3	.0333 (.0093)	.0322 (.0089)	.0336 (.0099)	
мнк	.0286 (.0099)	.0266 (.0130)	.0279 (.0101)	

Note: LS = Least-Squares, MG = M-Group

<sup>0 =</sup> No Adjustment, 1 = Adjustment with Present Data Base,

<sup>2 =</sup> Adjustment with truncated 1980 Youth Population, and

<sup>3 =</sup> Adjustment with full 1980 Youth Population.

MHK = Modified Heckman Adjustment.

Table 3

Root Mean Square Goodness-of-fit Statistics for Nine INDSCAL Solutions

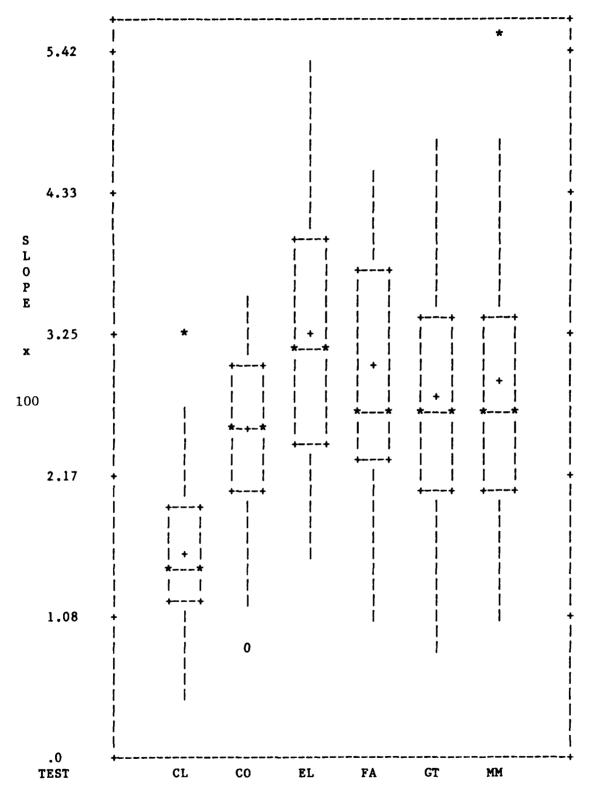
Adjustment		
Condition	STRESS	RSQ
LS0	.183	.737
LS1	.178	.759
LS2	.163	.832
LS3	.134	.883
MG0	.193	.729
MG1	.168	.781
MG2	.160	.836
MG3	.133	.884
MHK	.246	.427

Note: LS = Least-Squares, MG = M-Group

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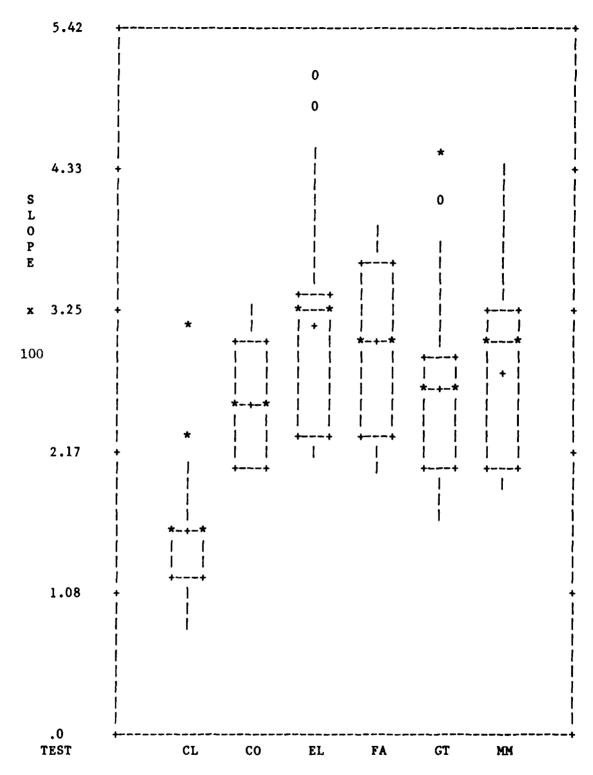
- 0 = No Adjustment, 1 = Adjustment with Present Database
- 2 = Adjustment with Truncated 1980 Youth Population, and
- 3 = Adjustment with Full 1980 Youth Population.

MHK = Modified Heckman Adjustment



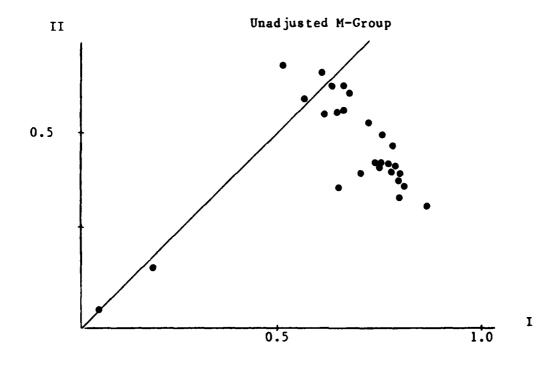
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Figure 1. Box-and-whisker plots of distributions of slopes from unadjusted least-squares analyses.



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Figure 2. Box-and-whisker plots of distributions of slopes from unadjusted m-group analyses.



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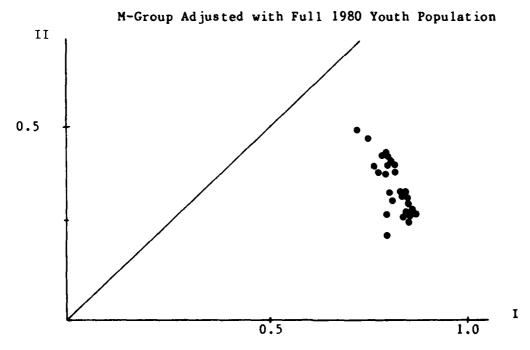


Figure 2. INDSCAL Weight Space for 27 Marine Corps Training Programs.

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